# PRIORITY-BASED RELIABLE ROUTING TECHNIQUES FOR WIRELESS BODY AREA NETWORKS

**SYNOPSIS**

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# PRIORITY-BASED RELIABLE ROUTING TECHNIQUES FOR WIRELESS BODY AREA NETWORKS

## 1. INTRODUCTION

This research primarily aims to develop a reliable and optimized routing techniques for prioritized healthcare data transmission in Wireless Body Area Networks (WBANs).

WBANs enable continuous monitoring of physiological data, facilitating early diagnosis and reducing unnecessary hospital visits. Advances in microelectronics and sensor miniaturization allow embedding sensors within the body, enabling health tracking without disrupting daily life. WBANs collect and transmit health data to medical servers, forming a feedback loop between patients and healthcare providers [1]. By 2050, over 2.1 billion people will be over 60, according to World Health Organization (WHO) [2]. This growing elderly population highlights the need for home-based healthcare. WBANs help by enabling early diagnosis, personalized care, and quick medical response, reducing pressure on traditional healthcare systems. However, important issues like data security and energy efficiency must be resolved if WBANs are to reach their full potential. Because these networks often rely on battery-powered equipment, their long-term operation depends on energy efficiency [3]. Robust security methods are necessary due to the sensitive nature of healthcare data. Thus, it is essential to establish prioritized data transfer, which guarantees that critical health data is sent first. To ensure reliable and long-lasting WBAN operation, secure and efficient data routing protocols are needed. These protocols should protect data privacy and save energy while handling prioritized health data.

## 2. LITERATURE SURVEY

Evolutionary-based Multi-hop Routing Protocol (EMRP) to optimize routing in WBANs by considering energy consumption, reliability, and network stability is proposed [4]. It ensures efficient energy usage and reliable data delivery through multi-hop communication. The protocol is well-suited for small-scale WBANs with limited nodes. However, its efficiency drops in larger networks due to increased computational overhead. An Intelligent Cluster-based Routing Protocol (ICRP) that utilizes two metaheuristic optimization algorithms Cuckoo Search for selecting optimal cluster heads and Harmony Search for determining the best routing paths from these cluster heads to the base station is presented [5]. This approach enhances the packet delivery ratio and improves the reliability of data transmission by ensuring optimal routing paths. However, the use of metaheuristic algorithms can result in longer processing times to achieve

optimal solutions, and in very large networks, the communication and computational overhead may become significantly high. In [6] the author introduced an African Buffalo Optimization (ABO) algorithm that plays a vital role in enhancing routing efficiency in Wireless Sensor Networks (WSNs). Inspired by the adaptive and cooperative behavior of African buffalo herds, ABO selects energy-efficient paths for data transmission, thereby conserving the limited battery power of sensor nodes. It dynamically adjusts routes based on network conditions, ensuring optimal path selection and continuous performance improvement. However, it requires multiple iterations to find the best path, making it slower for large-scale networks. Cooperative Energy-efficient Protocol with Relay node Allocation using Network coding (CEPRAN) integrated Cuckoo Search Optimization to identify optimal relay nodes and uses a Cooperative Random Linear Network Coding (CRLNC) approach for efficient data encoding at the relay node is presented in [7]. This protocol enhances energy efficiency and improves data transfer rates. However, its performance heavily depends on the cooperation of neighbouring nodes, and without such collaboration, the protocol's efficiency can significantly decline.

A Genetic Algorithm (GA)-based routing protocol is proposed in [8] enhances energy efficiency by selecting optimal routing paths through distance estimation between nodes under various scenarios. It offers benefits like routing optimization and dynamic energy management. However, it lacks focus on priority-based data, leading to less reliable and potentially delayed data transmission. Spider Monkey Optimization (SMO) algorithm is a swarm intelligence-based metaheuristic inspired by the foraging behaviour and social structure of spider monkeys is used in [9]. It employs a leader-based search strategy and dynamic group division to enhance exploration and exploitation in complex optimization problems. However, it may face challenges like local optima trapping and performance degradation in high-dimensional spaces without proper tuning.

Optimal Routing Algorithm (ORP) is utilized in [10] to enhance the data transmission of WBAN by selecting paths based on residual energy, link quality, and hop count, promoting efficient energy usage and robust network performance. It significantly reduces energy consumption and extends the operational lifetime of the network. However, the algorithm does not explicitly incorporate data prioritization strategies. This limitation can impact its effectiveness in emergency healthcare scenarios where critical data requires immediate attention. Improved QoS aware Routing Protocol (IM-QRP) implemented in [11] prioritizes data transmission in healthcare based on the criticality of the information. It effectively distinguishes between real-time vital signs and routine data, ensuring timely delivery of urgent information, thereby enhancing reliability and responsiveness. However, the protocol is low adaptability to

dynamic conditions. The Cramer-Shoup cryptosystem a public-key encryption scheme is utilized in [12], to provide security against adaptive chosen ciphertext attacks in network. It enhances the encryption scheme by integrating a hash-based verification mechanism and multiple group elements to ensure ciphertext integrity. However, its computational complexity is slightly higher due to additional encryption and verification steps.

In [13] the author proposed an energy-efficient routing protocol for WSNs utilizing Support Vector Machine (SVM) to enhance network longevity. An anomaly detection system for BAN in [14] uses IoT and machine learning to monitor physiological data. It uses various ML algorithms includes Logistic Regression (LR), AdaBoost and Extreme Gradient Boost (XGBoost) to identify deviations from normal patterns, indicating potential health issues. XGBoost-based fault detection is utilized in [15] to enhance data integrity and network reliability in WSNs by identifying sensor and communication faults. The model is trained on historical labelled data to differentiate between normal and faulty behavior and provides real-time fault predictions. Continuous learning with new data ensures high detection accuracy, proactive fault management, and improved network resilience.

### 2.1 GAPS IDENTIFIED THROUGH SURVEY:

The following key research gaps have been identified from the recent literature on WBANs:

1. **Missing integration of prioritization and routing**: Most algorithms lack dynamic routing based on data criticality and often overlook delay-sensitive prioritization strategies.
2. **Neglected Secure Priority Routing and Efficiency**: Security methods ignore routing-level protection for prioritized data; existing models are too complex for energy-limited WBAN devices.
3. **Limited Scalability and Optimization Trade-offs**: Algorithms are not scalable for multi-patient setups and rarely balance accuracy, prioritization, and energy efficiency.

## 3. OBJECTIVES OF THE RESEARCH

The main objectives of this research are to develop an energy-efficient WBAN by implementing a reliable routing algorithm integrated with data Prioritization to ensure Quality of Service (QoS).

1. To classify and prioritize physiological data based on the patient's health status and implement optimized routing for minimal-delay transmission to the coordinator node.

2. To provide secure and efficient routing of prioritized data from multiple patients, protecting critical health information from unauthorized access and tampering.
3. To improve performance in WBANs by using ML-based classification and prioritization, aiming to lower computational load, processing time, and energy usage.

Hence this doctoral research aims to propose algorithms for effective data prioritization, energy management, and reliable data transmission.

## 4. RESEARCH FRAMEWORK

The work is divided into three phases and the outline of the research work is illustrated in Figure 1.

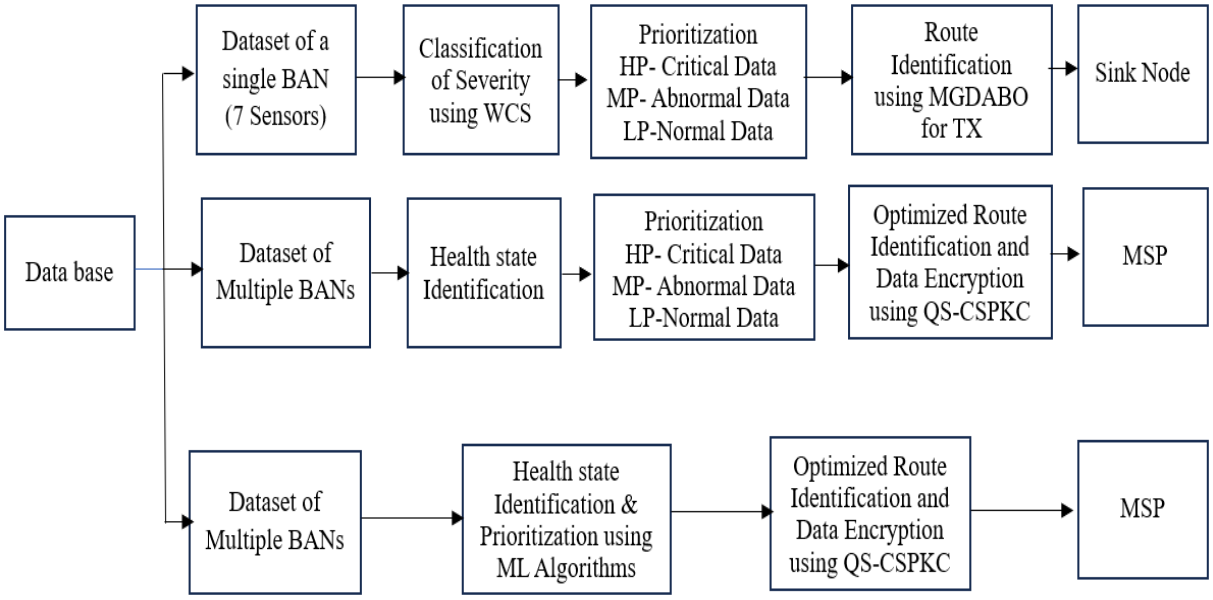
Data base
Dataset of a single BAN (7 Sensors)
Classification of Severity using WCS
Prioritization HP- Critical Data MP- Abnormal Data LP-Normal Data
Route Identification using MGDABO for TX
Sink Node
Dataset of Multiple BANs
Health state Identification
Prioritization HP- Critical Data MP- Abnormal Data LP-Normal Data
Optimized Route Identification and Data Encryption using QS-CSPKC
MSP
Dataset of Multiple BANs
Health state Identification & Prioritization using ML Algorithms
Optimized Route Identification and Data Encryption using QS-CSPKC
MSP

**Figure 1. Overview of the research work**

In Phase 1, the Multivariate Gradient Divergence African Buffalo Optimization (MGDABO) algorithm is used in a single WBAN setup. Seven physiological parameters such as temperature, heart rate, pulse rate, blood pressure, respiratory rate, oxygen saturation and pH level are considered for the study. The data is categorized based on its importance critical, abnormal, or normal. The MGDABO algorithm then finds the best transmission path to the sink node, aiming to reduce energy usage while ensuring that critical health data is delivered promptly.

Phase 2 introduces the Quantum Spider-Cramer Shoup Private Key Cryptosystem (QS-CSPKC). This phase builds on prioritized routing by adding a quantum-based method to classify the patient's health status at the sink node. It also uses Contention Access Period (CAP)-based

prioritization and ensures reliable routing to the Medical Service Provider (MSP) using the Spider Monkey-Cramer Shoup optimization method. The prioritized data is transmitted securely using encryption and routing techniques that protect data integrity while also conserving energy.

In Phase 3, Machine Learning (ML) models are added to the system to classify a patient's health condition before sending the data. Classifiers such as SVM, Bagged Trees (BT), and XGBoost) analyze the sensor data and label the patient's health as normal, abnormal, or critical. Based on this classification, the data is prioritized, and the QS-CSPKC protocol is used to securely transmit it. By combining ML with secure and prioritized routing, this phase helps build a smart and efficient healthcare system.

## 4.1 ENERGY EFFICIENT MULTIVARIATE GRADIENT DIVERGENCE AFRICAN BUFFALO OPTIMIZATION

In a single WBAN, data collected from sensors includes temperature, blood pressure, heart rate, pulse rate, respiratory rate, pH level, and oxygen saturation. By categorizing the data as normal, abnormal, or critical, the system identifies which information needs to be transmitted immediately and which is to be delayed. Also, WBAN devices have limited battery power and storage. If all data is sent without assessing its importance, it leads to unnecessary energy consumption and slow down the overall system performance. The dataset for WBAN is collected from the Kaggle database (2021) [16]. Classification is used to prioritize sending only the most important data first, saving energy and reducing delays. The Winsorized Correlative Segmentation (WCS) method helps classify physiological data into normal, abnormal, and critical categories.

**Step 1- Winsorization :** Winsorization is a process used to stabilize data by replacing input values that fall outside a specified range with the nearest acceptable value within the percentile limits. It minimizes the impact of outliers by adjusting extreme values.

**Step 2-Thresholds for Vital Signs :** Vital signs are evaluated using medically accepted threshold standards, as shown in Table 1, from the WHO, National Institutes of Health (NIH), and the American Heart Association (AHA) [17-19].

**Table 1. Threshold Values of Physiological Parameters**

| | Temperature (°C) | Heart Rate (BPM) | Pulse Rate (BPM) | Blood Pressure (mmHg) | Respiratory rate (breaths/min) | Oxygen Saturation ($SpO_2$) (%) | pH level |
|---|---|---|---|---|---|---|---|
| **Normal** | 35.1 to 38.0 | 60-100 | 60-99 | 90-120 (Systolic) 60-80 (Diastolic) | 12-20 | 95-100 | 7.3-7.5 |
| **Abnormal** | 38.1 to 39.0 or < 35 | < 60 or >100 | < 60 or >100 | 121-139 (Systolic) 81-89 (Diastolic) | < 12 or > 20 | 76-94 | <7.3& >7.4 |
| **Critical** | > 39 or < 35 | < 40 or >120 | < 60 or >100 | ≥ 140 or ≤ 89 (Systolic) ≥ 90 or ≤ 59 (Diastolic) | < 8 or > 30 | < 75 | <7.0 & >7.8 |

**Step 3 - Correlation Analysis:** The correlation between parameters is computed using Equation 1.

$$WCS = \frac{\sum_{i=1}^{n}(pd_i - T_{pd})}{\sigma} \quad and\ \sigma = \frac{1}{n}\sqrt{(pd_i - t_{pd})^2} \tag{1}$$

In Equation 1, WCS indicates correlation coefficient, $pd_i$ sensed data, $t_{pd}$ threshold value for a health condition, and n is the volume of data.

**Step 4 - Segmentation by Severity:** The WCS output with prioritization is indicated in Equation 2

$$WCS = \begin{cases} +1; & Normal \\ 0; & Abnormal \\ -1; & Critical \end{cases} \rightarrow \begin{cases} HP \rightarrow Critical\ data \\ MP \rightarrow abnormal\ data \\ LP \rightarrow normal\ data \end{cases} \tag{2}$$

- **Normal (+1 priority):** Data within normal range.
- **Abnormal (0 priority):** Data in the abnormal range.
- **Critical (-1 priority):** Data in the critical range indicating severe condition.

**Step 5 - Data transmission through MGDABO:** After prioritization, the MGDABO technique facilitates energy-aware data transmission based on priority by integrating Bregman Divergence with African Buffalo Optimization to the sink node.

- **Initialization of Nodes**: Sensor nodes are treated as buffaloes in the network. Each node is initialized with its energy level, location, and ID. The sink node broadcasts its location, and each biosensor node shares its location and energy level, enabling nodes to understand network topology.
- **Fitness Calculation with Multivariate Gradient**: A multi-objective fitness function is calculated for each node using parameters such as residual energy, link reliability,

distance to the sink, and channel capacity. Nodes with higher energy and stable links are prioritized.

- **Path Identification via Divergence Analysis**: Multiple paths are assessed using divergence techniques to measure how closely they align with optimal routing standards.
- **Buffalo Movement and Path Adjustment**: Based on gradient and divergence outcomes, each buffalo (node) periodically updates its routing path, gradually converging toward more efficient routes while considering bandwidth and reliability.
- **Optimal Path Selection and Convergence**: The algorithm iterates until the most efficient and least energy-consuming path is determined, ensuring that data from sensor nodes reach the sink node effectively.
- **Data Collection and Transmission**: Once the best path is established, data is collected by the control node.

### 4.1.1 RESULTS AND DISCUSSION

MATLAB 2022a is used to for testing. The quantity of patient data inputs ranges from 400 to 4000 in steps of 400, and energy usage is calculated accordingly. Figure 2 presents the energy consumption results for three methods: the proposed EEMGDABO, and the existing CEPRAN [7] and GA [8] approaches.

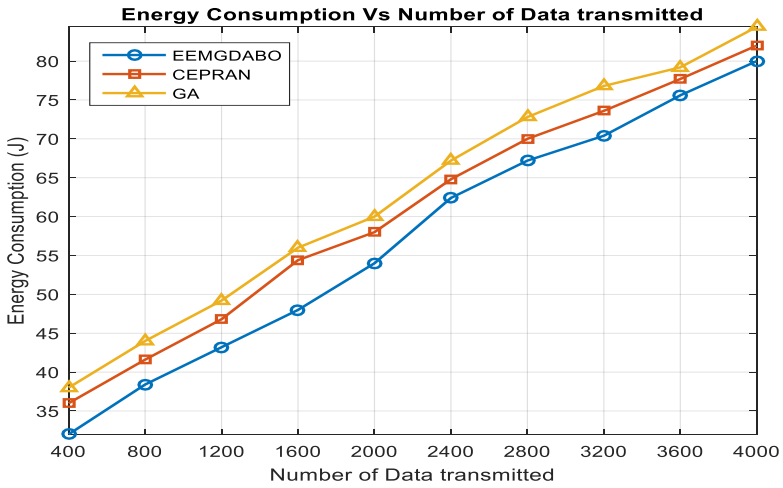


**Figure 2. Energy consumption of EEMGDABO, CEPRAN, and GA**

The X-axis represents the number of transmitted data samples, while the Y-axis indicates energy consumption. The proposed EEMGDABO consistently outperforms the other methods by selecting energy-efficient routes and nodes. For 400 data samples, the energy consumption is 32J with EEMGDABO, compared to 36J with CEPRAN and 38J with GA. Overall, EEMGDABO reduces energy usage by 6% compared to CEPRAN and by 15% compared to GA.

## 4.2 QUANTUM SPIDER CRAMER SHOUP PUBLIC KEY CRYPTOSYSTEM (QS-CSPKC) METHODOLOGY

The QS-CSPKC integrates the Cramer-Shoup Public Key Cryptosystem with the Quantum Spider Monkey Optimized Priority-aware Routing (QSMOPR) algorithm, combining robust encryption with intelligent, priority-based routing from the sink node to the MSP.

**Step 1 - Initialization – Data Collection and Normalization:** Physiological data such as temperature, heart rate, pulse rate, blood pressure, respiratory rate, oxygen saturation and pH level for multiple patients are collected. Z-score normalization is applied to standardize each vital sign, ensuring uniformity for analysis and comparison.

**Step 2 – Formulation of Input Vector Matrix:** An Input Matrix (IM), as in Equation 3 is constructed. Each row corresponds to a patient with their 7 physiological parameters

$$IM = \begin{bmatrix} P_1F_1 & P_1F_2 & \dots & P_1F_7 \\ P_2F_1 & P_2F_2 & \dots & P_2F_7 \\ \dots & \dots & \dots & \dots \\ P_4F_1 & P_4F_2 & \dots & P_4F_7 \end{bmatrix} IM = \begin{bmatrix} 37.0 & 72 & 75 & 120 & 16 & 98 & 7.4 \\ 38.2 & 90 & 88 & 135 & 22 & 95 & 7.3 \\ 36.5 & 60 & 62 & 110 & 18 & 99 & 7.5 \\ 37.5 & 80 & 78 & 125 & 20 & 96 & 7.4 \end{bmatrix} \quad (3)$$

**Step 3 - Patient Data Classification and Prioritization using Fitness Function:** IM is compared with the standard physiological threshold value in Table 1. Classification is based on defined thresholds for each vital parameter. The severity of a patient's data is assessed by the fitness function, which is indicated as N for normal, A for abnormal, and C for critical. Final prioritization is assigned as per Equation 4.

$$Prioritization = \begin{cases} +1 & Normal \\ 0 & Abnormal \\ -1 & Critical \end{cases} \quad (4)$$

**Step 4 - CAP Allocation:** Based on this, it puts the data in the right time slot. Critical data is sent first, then abnormal, and finally normal.

**Step 5 - Spider Monkey Optimization for Path Identification:**

- Start with 50 WBANs, each trying different paths to send healthcare data to the MSP.
- Evaluate each path based on delay, energy, and how important the data is (critical, abnormal, normal).
- Form groups (subgroups) of WBANs to explore better routes by learning from each other (like spider monkeys in troops).
- Update paths based on the best-performing WBANs in each group (local leaders) and overall best (global leader).

- Repeat until all WBANs choose the shortest, most energy-efficient, and fastest path for sending their data.

**Step - 6 Cramer-Shoup cryptosystem:** Before sending data, encryption is done by using the Cramer-Shoup cryptosystem at the sink node and decryption at the MSP.

- **Key Generation**: A public and private key pair using large prime numbers and group elements is created.
- **Encryption**: The packet (healthcare data) is converted into a secure ciphertext using the public key.
- **Hashing**: A hash of parts of the ciphertext is generated to ensure message integrity.
- **Data transmission:** Ciphertext is generated and transmitted through the shortest path
- **Decryption**: Using the private key the original data from the ciphertext is recovered
- **Verification**: The hash is checked to confirm that the message has not been altered

This integrated approach ensures fast and prioritized delivery of critical healthcare data in WBANs.

### 4.2.1 RESULTS AND DISCUSSION

Figure 3 shows that the proposed QS-CSPKC method achieves lower average energy consumption compared to the ORP and IM-QRP methods.

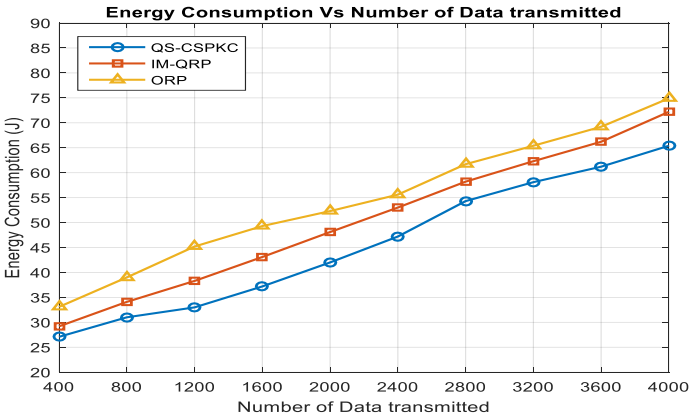


**Figure 3. Energy consumption of QS-CSPKC, ORP and IM-QRP**

By utilizing QSMOPR for optimal routing even in the presence of obstacles, QS-CSPKC reduces energy usage by 17% and 9% compared to ORP [10] and IM-QRP [11], respectively.

## 4.3 ML-ENABLED PRIORITY BASED ENERGY-EFFICIENT AND RELIABLE HEALTHCARE DATA TRANSMISSION

SVM, BT, and XGBoost ML models enable efficient classification of healthcare data into critical, abnormal, and normal categories for priority-based transmission, with minimal computational overhead.

### 4.3.1 Classification using SVM

SVM is a supervised learning algorithm that finds the optimal hyperplane to separate classes.

**Step 1:** Each patient's health record includes features like temperature, heart rate, pulse rate, blood pressure, respiratory rate, oxygen saturation and pH level are the input. The Principal Component Analysis (PCA) is utilized to reduce dimensionality and keep only relevant features.

**Step 2:** The SVM model is trained on 10Labeled patient data (e.g., Normal, Abnormal, Critical) to learn patterns and boundaries between health conditions.

**Step 3:** If the data is not linearly separable (which is common in healthcare), the Radial Basis Function (RBF) kernel helps map it to a higher-dimensional space for better separation.

**Step 4:** When patient data comes in, the trained SVM classifies it into one of the health categories as critical, abnormal, or normal based on the decision boundary.

### 4.3.2 Classification using BT

BT improves the stability of decision trees by combining the results of multiple trees.

**Step 1**: Multiple subsets of the training data is generated using bootstrap sampling (random sampling with replacement). Each subset captures different patterns in the data.

**Step 2:** A decision tree is trained for each bootstrap sample. The trees learn relationships between physiological data and severity labels (normal, abnormal, critical).

**Step 3:** The trained decision trees are used to predict the severity of a patient's condition.

**Step 4:** Severity Classification Output – Abnormal, Normal and Critical

### 4.3.3 Classification using XGBoost

XGBoost means Extreme Gradient Boosting, a powerful, fast, and scalable ML algorithm, especially good performance for classification.

**Step 1:** Patient data is collected and cleaned by handling missing values. Labels such as "normal," "abnormal," and "critical" are encoded numerically. The dataset is then split into training and testing sets.

**Step 2:** An XGBoost classifier is initialized and trained using gradient boosting, where each tree corrects errors made by the previous one. This sequential learning improves accuracy, and regularization helps avoid overfitting.

**Step 3:** The trained model predicts patient health status on new data. Then the performance of three ML models is evaluated using metrics like accuracy, precision, recall, F1-score, and

a confusion matrix to ensure reliability. Through this evaluation, XGBoost is identified as the best classifier compared to SVM and XGBoost.

**Step 4: Prioritized Data Transmission using QS-CSKC**

Once the patient data is classified (normal, abnormal, critical), it is assigned priority levels accordingly. The QS-CSPKC algorithm is then used to select the most energy-efficient and reliable route for transmission based on the priority and network conditions.

### 4.3.4 RESULTS AND DISCUSSION

**Performance analysis of SVM, BT and XGBoost**

**Figure 4. Performance Metrics of the classifiers – SVM, BT and XGBoost**

The classification performance metrics for SVM, BT, and XGBoost in Figure 4. demonstrate the effectiveness of ML models. XGBoost and BT are chosen to integrate with QS-CPKC because of its high accuracy. These algorithms offers faster and more optimized performance over than SVM making it well-suited for healthcare data analysis, and significantly reduces energy consumption.

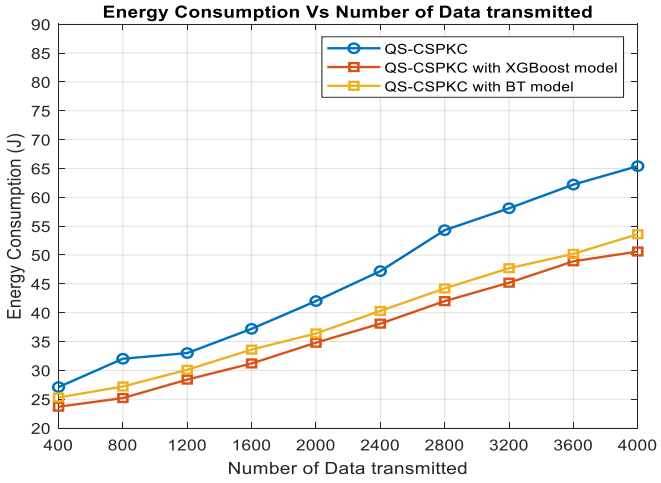


**Figure 5. Energy Consumption of QS-CSPKC, QS-CSPKC-BT and QS-CSPKC-XGBoost**

The energy consumption across data sizes ranging from 400 to 4000 is shown in Figure 5. QS-CSPKC with XGBoost consistently consumes less energy than both the standard QS-CSPKC and QS-CSPKC with BT. Overall, XGBoost achieves 5% lower energy consumption compared to QS-CSPKC-BT and 18% lower compared to the standard QS-CSPKC, thereby enhancing energy efficiency and extending network lifetime.

## 5 CONCLUSION AND FUTURE WORK

The main goal of this research is to develop an efficient algorithm for WBANs by combining data prioritization and optimal routing to maintain Quality of Service (QoS). The proposed EE-MGDABO algorithm for a single BAN uses the WCS technique and reduces energy consumption by 6% compared to CEPRAN and 15% compared to GA. It also lowers data loss by up to 4% compared to both CEPRAN and GA. For multiple BANs, the proposed QS-CSPKC algorithm ensures secure and priority-based data transmission. It reduces energy use by 9% compared to IM-QRP and 17% compared to ORP, while cutting packet loss by 5% compared to ORP and 11% compared to IM-QRP. When XGBoost is integrated with QS-CSPKC, it achieves 99.25% classification accuracy, lowers system complexity, reduces energy use by 18%, and decreases end-to-end delay by up to 6% compared to the standard QS-CSPKC. Overall, the proposed approach is well-suited for secure and energy-efficient healthcare monitoring using WBANs.

Future work will focus on testing the framework in operational environment using actual WBAN hardware. It is important to support mobility and smooth communication for continuous patient monitoring. Improving energy efficiency, reducing delay, and strengthening data security in such conditions are key goals. These improvements will help make WBANs more reliable and suitable for large-scale, real-time healthcare use.

## 6. ORGANIZATION OF RESEARCH

**Chapter 1** describes the WBAN architecture, challenges, and implementation issues in detail. **Chapter 2** presents and analyses the literature survey related to this research work. **Chapter 3** explains the implementation of the proposed Energy Efficient Multivariate Gradient Divergence African Buffalo Optimization (EEMGDABO) algorithm for a single WBAN setup and discusses the results in detail. **Chapter 4** discusses the implementation of the proposed Quantum Spider-Cramer Shoup Private Key Cryptosystem (QS-CSPKC) for multiple BANs and its corresponding results. **Chapter 5** presents various machine learning-based classifiers integrated with QS-CSPKC and details their performance results. **Chapter 6** concludes the research work and outlines the future scope of the study.

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**1.** Menaga, S., and R. Vanithamani. "Quantum spider prioritized routing and Cramer Shoup crypto secured data transmission in wireless body area network." Measurement: Sensors 30 (2023): 100897. **(Scopus)**

**2.** Menaga, S., and R. Vanithamani. "Energy efficient and reliable data transmission in WBAN using multivariate gradient divergence African buffalo optimization." International Journal of Communication Systems 38, no. 4 (2025): e5999. **(SCIE)**

**3.** Menaga S., and R. Vanithamani. "ML-based prioritized and reliable routing and Cramer Shoup Crypto secured data transmission in wireless body area network." International Journal of Communication Systems **(Communicated)**

### International Conferences

1. Menaga, S., R. Vanithamani, "A comprehensive review on wireless body area network-technologies, challenges, application, and energy saving techniques." In 2022 3rd International Conference on Electronics and Sustainable Communication Systems (ICESC), pp. 541-548. IEEE, 2022. **(Scopus)**
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